BUSINESS INTELLIGENCE AND
DATA ANALYTICS

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Introduction to Large Language Models

What is a Large Language Model (LLM)?

A Large Language Model (LLM) is a type of artificial intelligence system based on neural networks that has been trained on vast amounts of text data to understand and generate human language.

Key Characteristics:

- **Statistical nature**: LLMs learn patterns and relationships in language through statistical analysis of billions of words
- **Predictive models**: At their core, LLMs are trained to predict the next word (or token) in a sequence
- **Scale**: These models contain billions or hundreds of billions of parameters (the weights and connections in the neural network)
- **Generalization**: Through training on diverse data, LLMs develop the ability to perform many language tasks without being explicitly programmed for each one

How They Differ from Traditional AI:

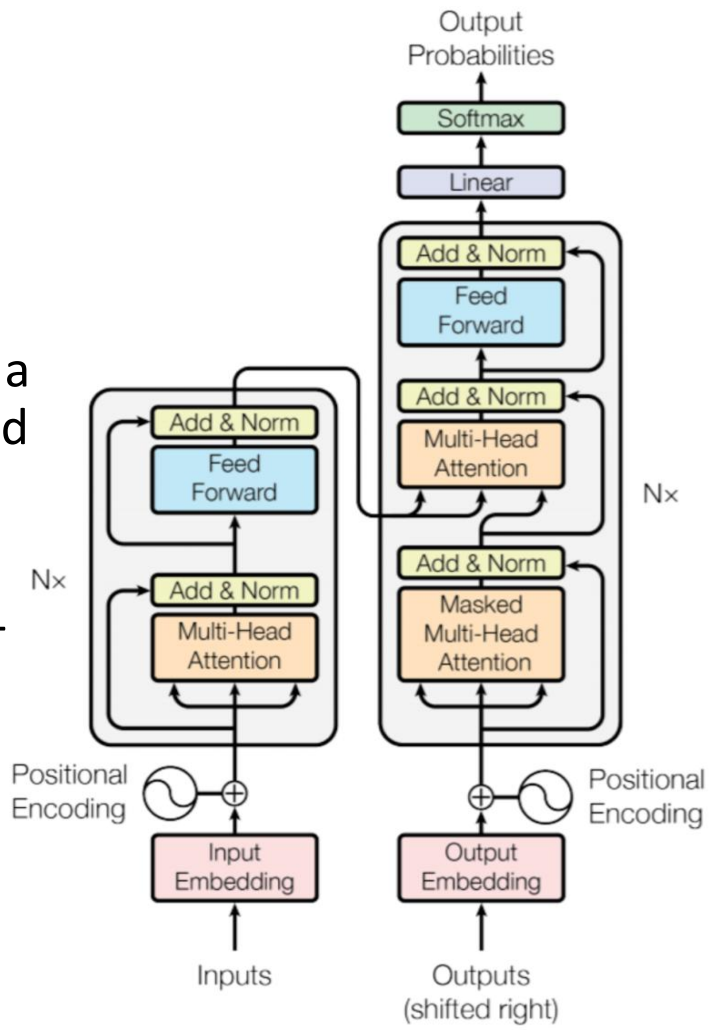
- Traditional NLP systems relied on hand-crafted rules and explicit programming
- LLMs learn directly from data without explicit rules
- They can handle the nuance, ambiguity, and complexity of human language
- They demonstrate emergent capabilities that weren't explicitly programmed

Transformers – Architecture and Principles

The transformer model consists of two main parts:

1. **Encoder:** The encoder processes the input sequence and generates a continuous representation of it. This representation captures the contextual information of the input tokens.
2. **Decoder:** The decoder takes the encoder's output and generates the final output sequence. It does this by predicting one token at a time, using the encoded representations and previously generated tokens.

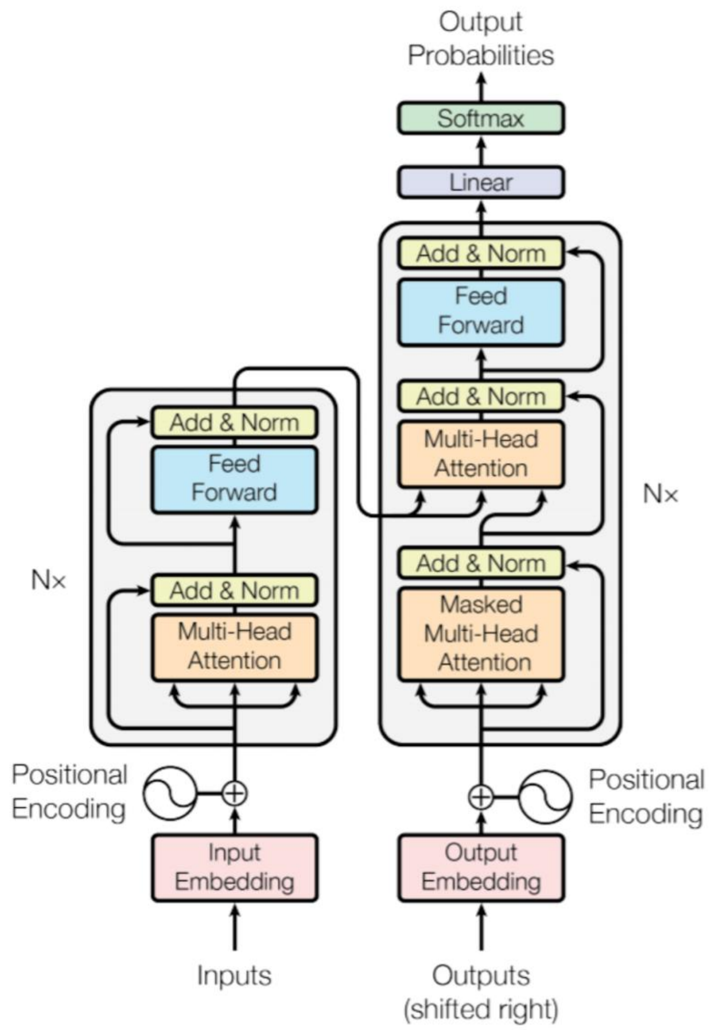
Both the encoder and decoder are composed of multiple identical layers—typically six layers in the original transformer architecture—allowing for deep learning and complex feature extraction.



Transformers – Architecture and Principles

Transformer Components:

1. **Embeddings**: Convert tokens to vector representations
2. **Positional Encoding**: Adds position information
3. **Multi-Head Attention**: Processes relationships from multiple perspectives
4. **Feed-Forward Networks**: Process each position independently
5. **Layer Normalization**: Stabilizes training
6. **Residual Connections**: Helps with gradient flow



A Summary of how the Transformer Works

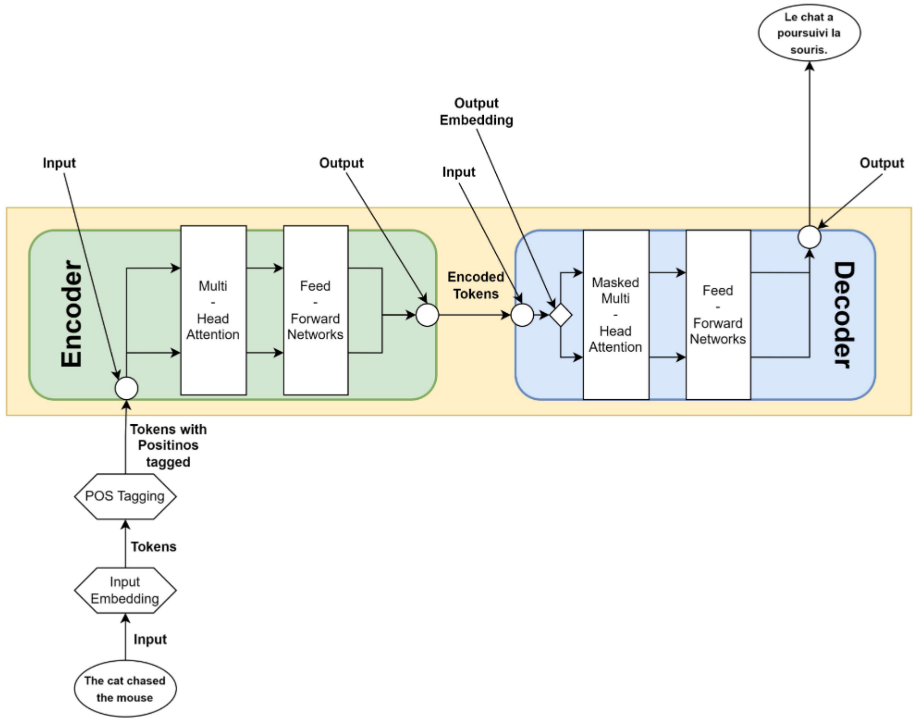
Input Sentence: "The cat chased the mouse."
Input Encoding:
- Break down the sentence into tokens (words).
- Convert each token into a numerical representation called an embedding.
- Add positional encodings to the embeddings to provide information about the position of each token.

Encoder Processing:
- The encoder takes the input embeddings with positional encodings.
- Pass the input through multiple layers of multi-head attention and feed-forward networks.
- Each encoder layer processes the input, allowing the model to learn complex representations of the sentence.
- The attention mechanism in the encoder learns relationships between tokens (e.g., "cat" is related to "chased" and "mouse").

Decoder Processing:
- The decoder takes the encoder’s output.
- Use masked multi-head attention to generate the output one token at a time.
- Attend to the encoder’s output to incorporate context from the input sentence while generating the translation.
- The attention mechanism in the decoder focuses on relevant parts of the input (e.g., the representation of "cat" when generating "Le chat").

Output Generation:
- The decoder generates the output sequence token by token.
- For the example, it generates: “Le”, “chat”, “a”, “poursuivi”, “la”, and “souris”.
- The complete French translation is: “Le chat a poursuivi la souris.”

Key Advantages:
- Process the entire input sequence simultaneously.
- Use attention mechanisms to capture relationships between tokens.
- Efficiently translates sentences, even with long-range dependencies.



Context Aware Embeddings

Contextual Word Embeddings (BERT and GPT)

Key Innovation

Unlike static embeddings (Word2Vec, GloVe), contextual models generate **different vectors for the same word** depending on its context.

Approach

- Uses deep, pre-trained neural networks (often transformer-based)
- Embeddings are derived from entire sentences, capturing syntax and semantics dynamically

Examples

- **BERT - Bidirectional Encoder Representations from Transformers (2018)**: Transformer-based neural networks trained with masked language modeling and next sentence prediction
- **GPT - Generative Pre-training Transformer (2018):** Transformer-based unidirectional language model focused on generation.

Characteristics

- Embeddings are **context-sensitive** (e.g., “bank” in “river bank” vs. “savings bank”)
- Each word is embedded based on its role in the sentence.
- Embeddings vary for the same word depending on its position and meaning.
- Significantly improve performance on downstream NLP tasks.

BERT: Bidirectional Encoder Representations from Transformers

- Developed by Google in 2018
- A **pre-trained language model** based on the **Transformer encoder**
- Reads text **bidirectionally**, enabling deep contextual understanding

Key Ideas

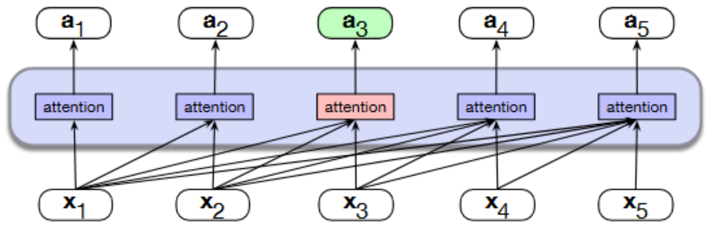
- Uses only the **encoder** stack of the Transformer
- Pre-trained on large text corpora, then fine-tuned on specific tasks

Pretraining Objectives

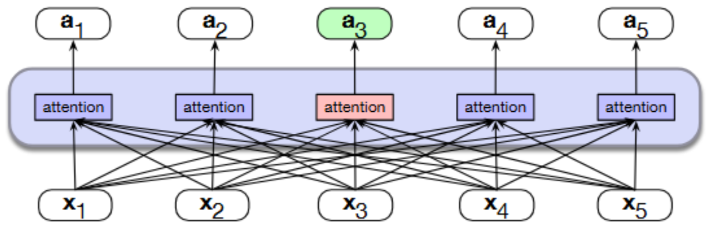
- **Masked Language Modeling (MLM)**: Predict randomly masked words in a sentence
- **Next Sentence Prediction (NSP)**: Predict if one sentence follows another

Applications

- Sentiment Analysis
- Question Answering
- Named Entity Recognition
- Text Classification
- Semantic Search



a) A causal self-attention layer



b) A bidirectional self-attention layer

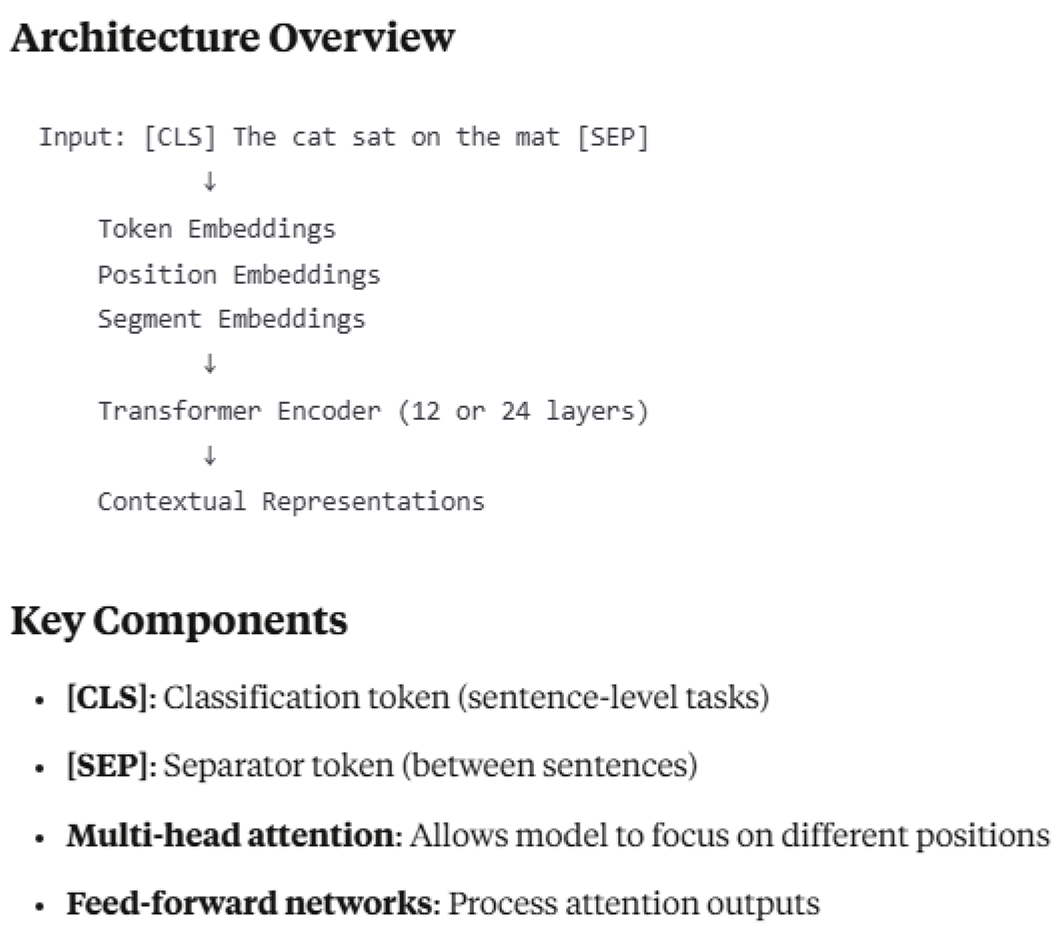
More About BERT

Key Advantages

- Contextual embeddings: Word meanings change based on context
- Captures long-range dependencies
- Pre-trained on massive datasets → Transfer learning
- State-of-the-art performance on 11 NLP tasks when released

How BERT Works:

- **Multiple stacked encoder layers** with self-attention mechanisms
- **No decoders** - purely focused on understanding input
- **Captures relationships** between words and their context
- **Powerful context learning** - understands word relationships in sentences
- **Meaningful representations** - transforms text into useful numbers



Architecture Overview

```
Input: [CLS] The cat sat on the mat [SEP]
              ↓
    Token Embeddings
    Position Embeddings
    Segment Embeddings
              ↓
    Transformer Encoder (12 or 24 layers)
              ↓
    Contextual Representations
```

Key Components

- **[CLS]**: Classification token (sentence-level tasks)
- **[SEP]**: Separator token (between sentences)
- **Multi-head attention**: Allows model to focus on different positions
- **Feed-forward networks**: Process attention outputs

BERT's Training Data

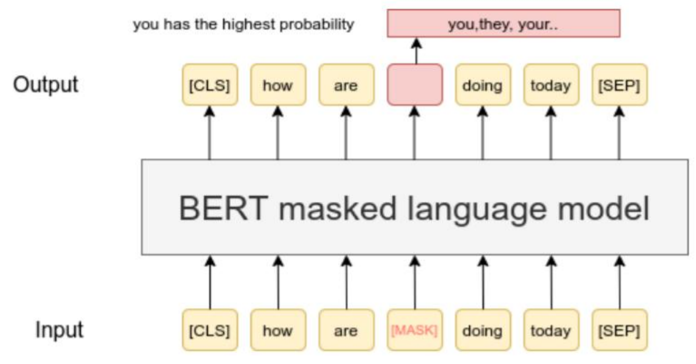
Pre-training Foundation

- **Training corpus**: 3+ billion words
  - English Wikipedia
  - ~10,000 unpublished books
- **Clean, large-scale dataset** for comprehensive language learning
- **Pre-training approach** to learn language patterns and context

Training Objective 1 - Masked Language Modeling

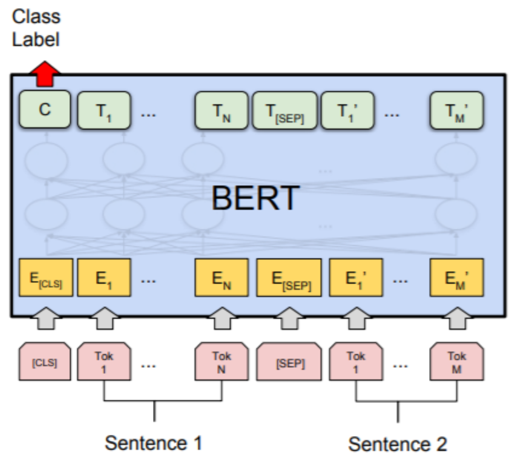
Learning Through "Fill in the Blanks"

- **Random word masking**: Some words are hidden during training
- **Context-based prediction**: BERT predicts masked words using surrounding context
- **Example**: "I love eating _____ in my fruit salad" → "lemons"
- **Key benefit**: Learns word relationships and contextual understanding
- **Powerful concept**: Used in many other AI applications



Training Objective 2 - Next Sentence Prediction

- **Title: Understanding Sentence Relationships**
- **Sentence pair analysis**: Given two sentences, determine if B follows A
- **Logical connection assessment**: Analyzes context and content
- **Example**:
  - A: "The cat climbed the tree"
  - B: "It was trying to catch a bird" ✓ (follows logically)
  - C: "The weather is nice today" ✗ (unrelated)
- **Note**: Later removed in newer models (MLM proved sufficient)



(a) Sentence Pair Classification Tasks: MNLI, QQP, QNLI, STS-B, MRPC, RTE, SWAG

BERT's Ideal Use Cases

Where BERT Excels

- **Text Classification**: Sentiment analysis, topic classification, spam detection
- **Named Entity Recognition**: Identifying people, organizations, locations, dates
- **Extractive Question Answering**: Finding answers within provided context
- **Semantic Similarity**: Measuring similarity between sentences/paragraphs
- **Key advantage**: Perfect for understanding tasks, not generation

Extractive Question Answering Example

How BERT Answers Questions:

- **Process**: Analyzes both context and question
- **Method**: Identifies start and end tokens of the answer
- **Example**:
  - Context: "Mount Everest is the highest mountain..."
  - Question: "What is the highest mountain?"
  - Answer: "Mount Everest" (extracted, not generated)
- **Important**: BERT extracts existing text, doesn't generate new content

Component	**BERT-Base** (L=12, H=768, A=12)	**BERT-Large** (L=24, H=1024, A=16)
Embedding Layer - Token + Positional + Segment	30522 × 768 + 512 × 768 + 2 × 768 ≈ 23.8M	30522 × 1024 + 512 × 1024 + 2 × 1024≈ 31.4M
Self-Attention - Q/K/V + Output per layer	$4 \times H^2 = 4 \times 768^2 = 2.36M$	$4 \times 1024^2 = 4.19M$
Total across all layers	12 × 2.36M = 28.3M	24 × 4.19M = 100.6M
Feedforward - Two linear layers per layer	768 × 3072 + 3072 × 768 = 4.71M	1024 × 4096 × 2 = 8.39M
Total across all layers	12 × 4.71M = 56.5M	24 × 8.39M = 201.4M
LayerNorms - Two per layer	2 × 768 = 1.5K × 12 = 18K	2 × 1024 × 24 = 49K
Pooler - Final CLS output to 768 or 1024	768 × 768 = 0.59M	1024 × 1024 = 1.05M
Total Parameters	**≈ 110M**	**≈ 340M**

- **L: number of layers (Transformer blocks)**
- **H: hidden size**
- **A: number of attention heads (H / A = size per head)**
- **Vocabulary size: 30,522**
- **FFN hidden size: 4×H (3072 for base, 4096 for large)**

BERT Variants

Common BERT Models

Model	Parameters	Layers	Hidden Size	Attention Heads
BERT-Base	110M	12	768	12
BERT-Large	340M	24	1024	16
DistilBERT	66M	6	768	12
RoBERTa	355M	24	1024	16
ALBERT	12M-235M	12-24	768-4096	12-64

Specialized Variants

- **BioBERT**: Biomedical text
- **SciBERT**: Scientific text
- **FinBERT**: Financial text
- **ClinicalBERT**: Clinical notes

Example: Print out BERT Embeddings

```
from transformers import BertTokenizer, BertModel
import torch

# Load pretrained BERT
tokenizer = BertTokenizer.from_pretrained('bert-base-uncased')
model = BertModel.from_pretrained('bert-base-uncased')

# Sentence
sentence = "He went to the bank to deposit money."

# Tokenize
inputs = tokenizer(sentence, return_tensors='pt')

# Get outputs
with torch.no_grad():  # No training, just inference
    outputs = model(**inputs)

# Get the hidden states (embeddings)
embeddings = outputs.last_hidden_state  # Shape: (batch_size, sequence_length,

# (hidden_size)
print(embeddings.shape)  # Example output: torch.Size([1, 11, 768])
```

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GPT – Overview and Architecture

What is Generative **P**re-trained **T**ransformer (GPT)?

- A family of **Transformer-based language models** developed by OpenAI
- Uses only the **decoder stack** of the original Transformer architecture
- Trained with **causal (autoregressive) language modeling** to predict the next token
- Focuses on generating human-like text (unlike BERT's understanding focus)

Training Objective

- Predict the next token in a sequence

GPT Variants

- **GPT-1 (2018, 120M Parameters)**: Introduced the pretrain-then-finetune paradigm
- **GPT-2 (2019, 1.5B Parameters)**: Scaled up model size, trained on web-scale data, Last publicly available weights
- **GPT-3 (2020, 175B Parameters)**: Enabled in-context learning, 100x boost, ~800GB file size
- **GPT-4 (2023, ~1T parameters (estimated))**: Multimodal, stronger reasoning and generalization

Applications (Wide range of NLP tasks through text generation)

- Text generation (e.g., chat, storytelling, code)
- Summarization
- Translation
- Question answering
- Semantic search and reasoning tasks

GPT's Architecture Deep Dive

How GPT Works

- **Multiple stacked decoder layers** with self-attention mechanisms
- **No encoders** - purely focused on text generation
- **Unidirectional processing** - considers only left-side context
- **Next word prediction** based on preceding words
- **High-quality text generation** from learned context patterns
- **Contextual understanding** combined with text creation capability

GPT Training Data

Pre-training Foundation

- **Massive, diverse datasets** including:
    - Web pages
    - Books and articles
    - Billions of words total
- **Different datasets** for each GPT version
- **Large-scale exposure** to language patterns and context
- **Quality varies** but emphasis on diversity and scale

Causal Language Modeling

GPT's Single Training Objective

- **Core task**: Predict the next word in a sequence
- **Method**: Uses context from preceding words only
- **Example**: "I love drinking fresh ___" → "lemonade"
- **Key benefits**:
    - Learns word relationships and context
    - Develops language patterns
    - Enables coherent text generation
- **Simplicity**: No masked language modeling or next sentence prediction

GPT's Ideal Use Cases

Where GPT Excels

- **Text Generation**: Story creation, creative writing, conversations
- **Instruction Following**: Responding to prompts and commands
- **Translation**: Converting text between languages
- **Summarization**: Creating concise summaries of longer texts
- **Code Generation**: Programming assistance and code completion
- **Versatile Applications**: Any task involving text output

Number of Parameters – GPT 3

Component	Parameter	Formula / Size	Total Parameters (Approx.)
Embedding Layer	Token Embeddings	Vocab × d_model = 50K × 12288	614.4M
	Positional Embeddings	n_ctx × d_model = 2048 × 12288	25.2M
Self-Attention (per layer)	Q, K, V, Output	4 × d_model × d_model = 4 × 12288^2	604.6M per layer
Feedforward (per layer)	2 layers (gelu)	d_model × d_ff + d_ff × d_model	1.2B per layer
LayerNorms (per layer)	Two per layer	2 × d_model	24.6K per layer
Total per layer	–	Self-attn + FFN + norms	≈ 1.8B per layer
Transformer Block Total	96 × 1.8B	–	≈ 172.8B
Final LayerNorm	–	d_model	12.3K
Output Layer (tied)	Shared with token embedding	–	— (tied with input embedding)
Total Parameters	–	Sum of above	**≈ 175B**

- **d_model = 12288**
- **n_layers = 96**
- **n_heads = 96 → each head has d_k = d_v = 128**
- **d_ff = 4 × d_model = 49152**
- **Vocabulary size ≈ 50,000**
- **Sequence length (n_ctx) = 2048**

GPT vs BERT Architecture

Aspect	GPT	BERT
Architecture	Decoder-only	Encoder-only
Text Processing	Unidirectional (left-to-right)	Bidirectional
Primary Goal	Text generation	Text understanding
Context	Previous words only	All surrounding words
Use Cases	Generation tasks	Classification/extraction

Training LLMs

What is LLM Training?

- LLM Training is the process of teaching a neural network to understand, generate, and manipulate human language.
- It involves feeding the model vast amounts of text data.
- The model learns patterns, grammar, context, and even some level of "knowledge" from this data.
- The goal is to adjust the model's internal parameters (weights and biases) to perform specific language tasks effectively.
- Modern models have BILLIONS of parameters (numbers) to learn during the training process.

Essential Components of LLM Training

1. **Dataset**: Large corpus of text data (e.g., books, articles, websites). Quality, quantity, and diversity are crucial.
2. **Model Architecture**: The neural network structure, predominantly the Transformer architecture (with self-attention mechanisms).
3. **Loss Function**: A function that measures the difference between the model's predictions and the actual target values (e.g., cross-entropy for next-word prediction).
4. **Optimizer**: An algorithm that updates the model's parameters to minimize the loss function (e.g., Adam, SGD).

The General Training Loop

1. **Data Preparation**: Collecting, cleaning, and tokenizing the text data into a format the model can understand.
2. **Model Initialization**: Setting initial random values for the model's parameters.
3. **Forward Pass**: Feeding input data through the model to get predictions.
4. **Loss Calculation**: Comparing predictions to the actual data to quantify error using the loss function.
5. **Backward Pass (Backpropagation)**: Calculating gradients, which indicate how each parameter contributed to the error.
6. **Parameter Update**: Adjusting model parameters using the optimizer in the direction that reduces the loss.
7. **Iteration**: Repeating steps 3-6 for many batches of data over multiple epochs (passes through the entire dataset).

Main Training Phases

1. LLM Pretraining.
2. LLM Fine Tuning

Pre-training: Building the Foundation

- The initial, most resource-intensive training phase.
- Models are trained on massive, diverse datasets (e.g., Common Crawl, Wikipedia, books).
- The objective of this step is to learn general language understanding, grammar, common sense reasoning, and factual knowledge.
- Usually self-supervised (e.g., predicting masked words, next sentence prediction).
- Results in a **base model** with broad capabilities.
- Examples: GPT-3, BERT, Llama pre-training.

Fine-tuning: Specializing the Model

- Takes a pre-trained base model and further trains it on a smaller, task-specific dataset.
- The objective of this step is to adapt the general knowledge of the pre-trained model to perform well on a particular downstream task (e.g., medical question answering, legal document summarization).
- It requires significantly less data and computation than pre-training.
- Can also be used for instruction tuning (following prompts) or aligning with human preferences (RLHF).

Data: The Critical Ingredient

- **Quantity**: LLMs require vast amounts of text to learn effectively. "More data is better" is often true, up to a point.
- **Quality**: Clean, well-formatted, and coherent data leads to better models. Garbage in, garbage out.
- **Diversity**: Exposure to various styles, domains, and perspectives helps create more robust and less biased models.
- **Preprocessing**:
  - **Tokenization**: Breaking text into smaller units (words, sub-words).
  - **Normalization**: Standardizing text (e.g., lowercasing, removing special characters).
  - Creating input IDs, attention masks.

Model Architecture: The Transformer

- The dominant architecture for state-of-the-art LLMs.
- Key Innovations:
  - **Self-Attention Mechanism**: Allows the model to weigh the importance of different words in a sequence when processing information, capturing long-range dependencies.
  - **Positional Encodings**: Injects information about the position of tokens in the sequence.
  - **Encoder-Decoder Structures** (for some tasks) or **Decoder-Only Structures** (common for generation).
  - **Feed-Forward Networks**: Applied independently to each position

Computational Demands & Challenges

- **Hardware**: Requires powerful GPUs (Graphics Processing Units) or TPUs (Tensor Processing Units) for parallel computation.
- **Distributed Training**: Often necessary to train large models across multiple GPUs or machines, adding complexity.
- **Time**: Pre-training can take weeks or months, even with significant computational resources.
- **Cost**: Significant expenses for hardware, cloud computing, and energy consumption.
- **Memory**: Model parameters and activations require substantial memory. Techniques like mixed-precision training help.

Ethical Considerations in Training

- **Bias Amplification**: Models can learn and perpetuate biases present in the training data (e.g., gender, racial, societal biases).
- **Harmful Content Generation**: Potential to generate misinformation, hate speech, or other harmful text.
- **Data Privacy**: Ensuring that sensitive information from training data is not memorized or leaked.
- **Environmental Impact**: Significant energy consumption of training large models.
- **Accessibility and Equity**: Ensuring benefits of LLMs are widely accessible.

LLM Training Details - More Recent Models & Considerations

Model (Version/Size)	Est. Data Size (Tokens)	Context Size (Max Tokens)	Est. GPUs / Compute	Est. Training Time	Est. Electricity / Carbon Footprint	Est. Training Cost
GPT-3 (Base models like Davinci)	~500 Billion - 1 Trillion (incl. C4, Wikipedia, Books, etc.)	2,048 (later models up to 4,096)	~10,000 V100 GPUs (for original run) / ~3.6M A100-equivalent hours (PaLM 540B reference)	~34 days (using 1,024 A100s, research estimate) - Several months (actual, unconfirmed)	~1,287 MWh (training) / ~552 tons CO_2eq (Patterson et al.)	\$4.6M - \$12M+ (compute, various estimates)
Llama 2 (All sizes)	2 Trillion	4,096	Reported 6,000 GPU-months (A100-80GB equivalent for the family) / 1.7M+ GPU hours for 70B	Jan 2023 - July 2023 (overall project, specific model run time shorter within this)	3.3M kWh (entire project) / 539 tons CO_2eq (training, 100% offset by Meta)	Significant (part of Meta's AI investment)
BLOOM (176B)	366 Billion (1.6 TB)	2,048	384 A100 GPUs	~3.5 - 4 months	~433 MWh (training) / ~25-55 tons CO_2eq (trained in France, low-carbon energy)	~\$2M - \$5M (compute, public estimates)

LLM Training Details - More Recent Models & Considerations

Model (Version/Size)	Est. Data Size (Tokens)	Context Size (Max Tokens)	Est. GPUs / Compute	Est. Training Time	Est. Electricity / Carbon Footprint	Est. Training Cost
GPT-4	Not officially disclosed (speculated >> GPT-3, likely multi-trillion)	8,192 (GPT-4-8k) & 32,768 (GPT-4-32k); GPT-4 Turbo: 128,000	Not officially disclosed (speculated tens of thousands of A100s/H100s)	~5-6 months (speculative estimates)	Not disclosed (Expected to be significantly higher than GPT-3; estimates range from 20,000-78,000 MWh & thousands of tons CO_2eq for comparable efforts)	Est. >$60M - $100M+ (compute, speculative)
Llama 3 (Instruct models)	>15 Trillion (for the Llama 3 family)	8,192 (some reports suggest up to 128k for future/experimental versions)	Significant clusters of H100s (e.g., Meta mentioned two 24k H100 clusters)	~3 days (8B), ~17 days (70B), ~97 days (est. for 400B+ on 16k H100s)	Llama 3.1 405B est. ~11 GWh. Carbon footprint not yet fully disclosed, but Meta aims for net-zero operations.	Very High (part of Meta's large AI infrastructure investment)
Gemini 1.0 (Pro/Ultra)	Not officially disclosed (multimodal, likely vast & diverse datasets)	32,768 (Gemini 1.0 Pro); Gemini 1.5 Pro: 1 Million (up to 10M experimental)	Trained on Google's TPU v4 and v5e pods (thousands to tens of thousands of TPUs)	Not publicly disclosed (likely months)	Not disclosed. Google emphasizes efficiency & use of renewable energy. Gemini 1.0 was reported to be more efficient than some predecessors.	Very High (part of Google DeepMind's core AI efforts)

Discussion / Q&A

- What are the biggest challenges in training even larger and more capable LLMs?
- How can we mitigate biases in LLM training data and subsequent models?
- What future advancements in LLM training do you foresee?

Fine-Tuning Large Language Models (LLMs)

What is Fine-Tuning?

- **Pre-training Phase**
  - Trained on large corpus using Masked Language Modeling (MLM) and Next Sentence Prediction (NSP)
- **Fine-Tuning Phase**
  - Fine-tuning is the process of continuing the training of a pretrained LLM on a smaller, task-specific dataset.
  - The objective is to specialize the model for a particular use case or domain.
- **Why Fine Tune LLMs?**
  1. Improve performance on specific tasks.
  2. Inject domain-specific knowledge (legal, medical, financial, etc.).
  3. Adapt to company-specific language or tone.
  4. Reduce inference cost by limiting model size and scope.
- **Use Cases of BERT Fine-Tuning**
  - Customer Support Chatbots (trained on company FAQs).
  - Legal Document Analysis.
  - Scientific Paper Summarization.
  - Code Assistants for specific frameworks.
  - Sentiment classification for product reviews.

Typical LLM Fine Tuning Workflow

1. Choose a Pre-trained Model

Pick a base model from Hugging Face (e.g., distilbert-base-uncased for classification or gpt2 for text generation).

2. Prepare Your Dataset

Format your data appropriately. Common formats:

- For classification: CSV with text and label columns.
- For generation: Text file or JSON with prompt and completion.

3. Tokenize the Data

Convert text into tokens the model understands using a tokenizer.

4. Define Training Arguments

Set training parameters like learning rate, batch size, and number of epochs.

5. Train the Model

Use a trainer to fine-tune the model on your dataset.

6. Evaluate & Save

Check performance and save the model for future use.

7. Share (Optional):

- Push your fine-tuned model back to the Model Hub.
- Create a demo in Hugging Face Spaces.

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